Benefits of Energy Management Systems on local energy efficiency, an agricultural case study

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***Abstract*—Energy efficiency is a concern impacting both ecology and economy. Most approaches aiming at reducing the energy impact of a site focus on only one specific aspect of the ecosystem: appliances, local generation or energy storage.**

A trade-off analysis of the many factors to consider is challenging and must be supported by tools. This paper proposes a Model-Driven Engineering approach mixing all these concerns into one comprehensive model. This model can then be used to size either local production means, either energy storage capacity and also help to analyze differences between technologies. It also enables process optimization by modeling activity variability: it takes the weather into account to give regular feedback to the end user. This approach is illustrated by simulation using real consumption and local production data from a representative agricultural site. We show its use by: sizing solar panels, by choosing between battery technologies and specification and by evaluating different demand response scenarios while examining the economic sustainability of these choices.

***Index Terms*—simulation, modeling, energy, economic analysis**

I. Introduction

Renewable energies currently benefit from numerous subsidies to promote their use so as to reduce greenhouse-gas emissions. Nevertheless, it seems worth **considering the cost-effectiveness of these solutions without these incentives**, as they are highly dependent on political will and can be questioned. The reduction in manufacturing costs, particularly in solar energy, suggests that these solutions can eventually compete with traditional sources if they are properly used. In this paper, our application domains are those of **agriculture and industry** in which it is possible to identify and influence consuming processes. We mainly consider local generation for **self-consumption purposes (microgrid)** as it limits infrastructure costs, minimizes line losses, reduces the need of the Grid and hopefully reduces the electricity bill.

Competitive low-carbon energy is hampered by the stochastic nature of these sources. During peak periods, the electricity produced is competitive, but too often, the scheduled consumption is not aligned with production. In practice, process planning was and is still driven by the electricity price from the grid. On average, the profitability of the installations is therefore not certain. In this context, *using battery to shift the load* looks appealing but is, as of today, *far from being economically viable* if not done properly.

Consequently, the achievement of a profitable self-production site is, in practice, a question of **trade-off that involves several factors**: the scaling of energy sources, the sizing of batteries used, the desired autonomy level, the ecological concerns, and the organization of demand. For example, high level of autonomy, that could be considered "eco-friendly", cannot be achieved without the use of a large number of batteries and energy sources: it is then very difficult to be profitable. This analysis is therefore highly dependent on the site, on the motivations of the stakeholders, on the structure of the activities, and on the flexibility given to these factors.

This trade-off analysis is very challenging: to be carried out effectively and comprehensively, it must be supported by tools that help the stakeholders. While much work has been done in the literature on the impacts of different factors, there are few approaches that offer a comprehensive model. In [1], we argued that model-driven engineering is suited for the development of such a model and we presented some preliminary implementation. We propose an **activity shifting approach** along with a **multi-factor simulator** to improve the energy efficiency of a particular site. The idea is also to provide guidance to stakeholders in adapting their industrial processes and their activities to better align consumption and production. In this paper, we present **a concrete use-case in the agricultural field**, and make a detailed analysis that shows that the use of simulation is required to explore all possible trade-offs. In particular, we show how the use of batteries alone cannot guarantee the sustainability of the installation, and we strive to find the levels of autonomy that are interesting from both an ecological and a profitability point of view.

This paper is structured as follow: Section II details the state of the art regarding local generation and energy management systems (EMS) and the complementarity of other approaches with our own. In Section III we present an overview of our approach based on the modeling of every site concerns: production, consumption, storage and activities. In Section IV, we present our case study based on **real world data from a specific site that we have instrumented**. We then evaluate by simulation every aspect individually to show their impacts on each others and the global sustainability of the site. We conclude this article in Section V and present our future work.

II. Related Work

Many approaches focus on one specific aspect of the energy efficiency issue: consumption, production or storage. **Consumption modeling approaches** [2] focus generally on one specific appliances type commonly found on most sites such as: water heater or HVAC. Human activities, their scheduling, and their energy consumption are often left out. We believe that it is possible to improve the guidance for the planning of these activities to better match them to the production periods.

Local production modeling and their integration into complete systems are very active fields of study [3]. In recent years techniques such as Machine Learning [4] or Support Vector Machine [5], [6] became more and more reliable and forecast at a shorter term than they used to. These techniques allow to grasp the unpredictability of renewable energies and ease their integration into automated systems.

Energy storage modeling [7] is also an active domain particularly regarding the use of batteries coupled with local production and in off-grid systems.

All these approaches provide tools to model or forecast each separate part of the system, but to our knowledge none provide a unified and comprehensive view of the system. Yet this vision is necessary for the stakeholders to be able to size the installations and adapt their industrial processes. Providing such a tool is the objective of our research. Bourgeois *et al.* [8] consider these kind of scenarios in a domestic context, leaving industrial context [9] more open to exploration. The main difference between residential sector and the industrial oni comes from the variability of both appliances and time of use [10]. Industrial sites have way more strict schedules, which makes it easier to forecast and plan new activities.

Optimization methods are traditionally oriented towards consumption on peak shaving [11], [12] or global reduction by avoiding idle time processes [13]. These methods are relatively easy to apply to self-consumption efficiency scenarios [14] but require adaptation. Our system is intended to be flexible enough to allow the use of these methods, which only focus on part of the system, into our comprehensive model.

Regarding **simulation**, implementations are often divided into two categories: pure simulation approaches and real world devices control. Simulations can help to create better scheduling [9], [15] that then need to be applied in real life. These simulations are usually written using R, Mathlab or Simulink. Other approaches [16] try to apply their optimization in real time to directly take actions in the real world. We intend to do both.

Our approach is therefore complementary: the use of the **Model Driven Engineering**, the proposal of a complete and extensible model, and the simulation and control capabilities of our systems help experts in their decision-making.

III. Approach of Site Modeling

A. Overview

Model Driven Engineering (MDE) techniques benefit Computational Science [17] by providing high-level tools to domain experts and let them manipulate concerns with their own word from their field of expertise. Most approaches in the literature focus on a particular aspect of the energy efficiency problems such as machines consumption optimization, local production energy forecasting, activity scheduling under constraints or storage charge cycles optimization. We propose to leverage MDE techniques to tackle this problem in a comprehensive way, merging existing approaches and thus help explore more optimization paths.

Our goal is to capture all the energy aspects of a site into a single general model: including local production, consumption and including the activities involved. This tool will help experts to size their energy storage and energy production system, and to provide activity shifting optimization based on various criteria — return on investment, self-consumption rate or grid autonomy for instance. It can be used prospectively or continuously: i) simulating long period in advance to support long-term sizing and decision-making or ii) to obtain continuous feedback over shorter periods.

1) Equipment sizing: The tool can be used before installing any equipment to size and estimate both production and storage capacity in order to reach a particular autonomy level or profitability. It allows experts to describe the different parameters of the simulation such as the physical appliances to include, the way they want it to be used, or their frequency of use. They can also specify the different types of energy sources used (e.g., solar or wind) and the storage technologies used (e.g., lithium or lead)

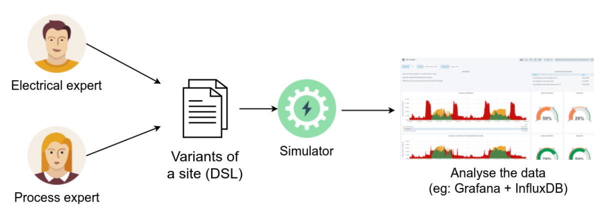


Fig. 1. Experts describe their simulations using our Domain Specific Language (DSL) and then see how it performed using graphical view and data analysis tools.

Figure 1 depicts a typical work flow where an electrical expert could describe the local generators in place and some electrical devices. Working on the same site, a process expert could describe the usage of these devices by the client and add the variability the user has or the variability his work can support with no impact on its quality. The description takes the form of a textual representation, written in a Domain Specific Language with dedicated tooling. In a single file, or multiple and including fragments, experts can describe a site along with its variants, one variant per "what-if" questions for instance. This file is then executed by our simulator and the results pushed to a visualization platform. This way the experts can precisely see the results in term of energy for each day of the simulation or just look at the daily or weekly results.

2) Activity optimization: The system also makes it possible to describe the schedule of the activities/processes and the machines they use. This can be done prospectively in coarse grain and then gradually refined continuously. Process variability modeling allows the simulator to optimize the scheduling of activities, within given constraints, to improve overall objectives such as: increasing the rate of self-consumption or minimizing the use of the grid. The results of optimization can be either feedback with new schedules for the end user or direct actions on real-world devices such as charging or discharging a battery. The Figure 2 shows the use of the system from the creation of the model, through the observation of the industrial site, to the creation of feedbacks from simulations.

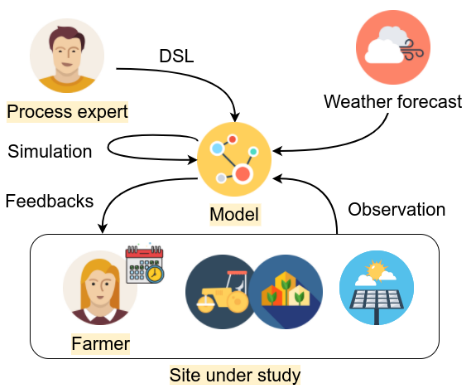


Fig. 2. In production our model can be used to give optimization feedbacks to the site owner by fetching the local weather forecast.

This objective can be tuned by the expert to achieve various goals: a) improving the self-consumption by prioritizing the local producers, b) reducing the electricity bill, c) improving the autonomy no matter the cost, or d) trying to balance these three aspects. Providing high-level tuning of such parameters is the key to understand and explore the electrical variability of a site.

Variability is a way of letting the system know that the usual schedule we specified can be modified by shifting it by a given amount of time. The system is then responsible to either take action on the physical devices or send recommendations to the final user. Figure 3 shows a particular day when the solar energy produced is in excess — depicted by the area in yellow. The system proposes to shift the load happening at 7:00am to 10:00am to use the energy available from the solar panels. The benefits are to improve the day's autonomy and reduce the energy excess. It is computed by simulating the final user schedule and fetching the weather forecast.

B. Details of our implementation

We organize all aspects of an industrial site around a class **Site** holding general information of the site. Then we separate energy producers, from consumers and from storage. Each of these aspects may represent real world machine or an equation abstracting it, depending on the purpose of the model. In addition to the representation of machines, we have added a representation of activities, both human and automated. Those activities describe how and when the machines are used in terms of frequency and seasonality. With those we can express recurring events and express more complex industrial processes sharing one machine for instance. In addition to this *variability* we also capture *flexibility*: how an activity can be altered, if it can be shorten, lengthen, if its intensity can be changed and finally if the whole process can be shifted. This flexibility can later be used by our system to determine if a change could benefit the whole system.

A description of an industrial site can be done by a process expert with our Domain Specific Language (DSL). A DSL makes easier the design phase of the simulation, experts can use predefined appliances or batteries or define their own based on their electrical specifications. Appliances can be defined and extended directly using the DSL or externally using Java programming language and then loaded as a plugin and referenced in the DSL.

The DSL and most of the simulator are implemented in Java with the help of the Eclipse Modeling Framework (EMF) and Xtext. Simulation results are computed during the simulations and pushed to a running Influxdb instance, a time series oriented database, for every steps the simulator performs. Specific metrics such as autonomy, self consumption, rate, total consumption and production are stored in a local database and can be queried to compare simulations between each others and help find the best configuration. Visualization tools allow the expert running the simulation to navigate in the data, to look for particular events in the simulation such as: empty batteries for several days or to look for the most autonomous day.

IV. Agricultural Case Study

Our work is carried out in collaboration with OKWind. The company is specialized in micro-generation and has developed expertise in vertical-axis wind turbines, photovoltaic trackers, batteries and heat pump. It proposes to deploy self-production units directly where the consumption is done. One of its objectives is also to guide farmers in the planning of their activities to get the most out of the energy produced. To this end, it also has expertise on livestock management constraints.

OKWind data are interesting because they are based on the observation and the instrumentation of numerous sites over

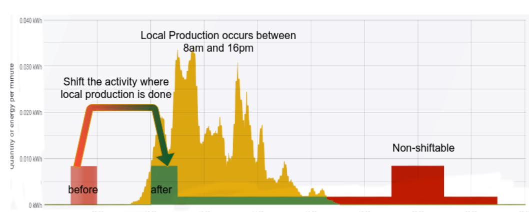


Fig. 3. Electric load used off production (7:00am) time are moved to reduce energy excess (at 10:00am)

the past ten years. In this paper, we focus on a particular farm in Brittany region, France. Farmers are good business partners where energy management experiments are at stake. They are usually located at the edge of the national grid infrastructure, more prone to blackouts. They usually run their own businesses and are willing to adapt their processes, to the extent that they benefit from this adaptation — electricity being one of their first line of expenditure, they gladly welcome any way to reduce it.

Site specifications. For this case study we selected a farm with solar trackers along with a power consumption meter installed since 2016. This site consumes on average 180MWh of electricity per year, which is roughly eleven times the consumption of a 100m^2 house of a family of 4 in France. Daily consumption distribution is shown in red in Figure 4 along with the production of one module of solar panels totalling 18kWp in green. The data were collected by MID (Measuring Instrument Directive) certified power meters at 5 minutes intervals. MID devices are certified for electricity billing so we know they are reliable for measurements. For this experiment, two years of data is appropriate because it will attenuate the seasonal impact of the weather on the data.

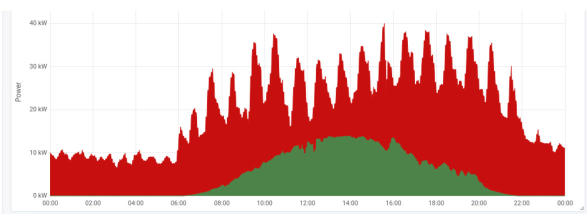


Fig. 4. Studied site typical daily consumption, in red, and production, in green, example for the day of May 21, 2017. Green area shows the day time period and we see that consumption tends to be higher during the day.

This site is a good candidate for solar generation: it has no days off because it deals with living beings and because part of the consumption comes from the ventilation it consumes, which is more during the day and in summer. During summer, day times are longer and energy production from solar panel more important.

In the following subsections, we propose to simulate different scenarios and to provide indications on the different possible compromises. First, a) we focus on energy supply alone, then b) we look at the impact of adding storage, and finally c) we analyze the possible gains through the restructuring of activity planning.

A. *Supply sizing*

The installation of solar trackers (or any renewable source of energy) on a site makes it possible to limit dependence on the grid. When energy is used efficiently, the electricity bill is reduced. Conversely, the energy excess is not usable and thus profitability might be very questionable. Finding the right sizing is therefore necessary. We focus on photovoltaics: mixing different renewable energy sources to extend production periods has been considered but is beyond the scope of this paper. OKWind mainly produces two axis solar trackers. They have the benefit to lengthen the production time period, flattening the noon production peak. Two axis solar panels produce 70% more energy in a year compared to roof installation and so are more suited for self-consumption.

Here we use our tool on the consumption data of the site and provide all the information concerning the production means using our DSL. Our objective is to estimate the maximum autonomy that can be achieved in a cost-effective way and to determine the appropriate size of the solar panel. To this end, we simulate different scenarios: we run the same two years of data and change the total power peak of the installation. This allows to assess the evolution of self consumption and autonomy and how the consumption impact them. Since we only rely on solar production we know that the consumption happening during the night will never be matched with a local production and thus that our autonomy cannot reach 100%.

Figure 5 is the result of seven successive simulations, from one single module of 18kWp, self consuming at 99% and putting the site 15% autonomous, to seven modules for a total of 125kWp self consuming at 40% and a 43.7% autonomous site. We see that installing more than 40kWp of solar panels do not do much on the autonomy while greatly reducing the self consumption of the installation. From this simulation we derive two information: a) due to the night consumption, the maximum autonomy achievable with solar panels in our selected farm is around 40%, b) it is therefore useless to install more than 40kWp on site if we do not plan to use other measures.

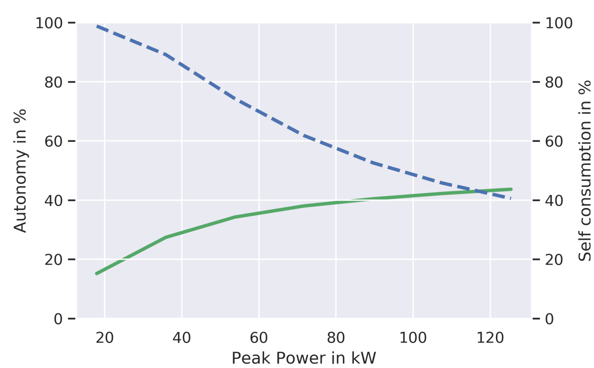


Fig. 5. Self-consumption and autonomy rates evolution for various installation sizes without storage capacity. Here the increase in autonomy is marginal beyond 60kW because night activities are always powered by the grid. Similarly, self-consumption decreases: these activities do not use renewable energy, which causes an unconsumed surplus.

On the basis of these simulations, it is possible to estimate the amortization of different installation sizes, taking into account their installation costs, the different grid tariffs (0.15€/kWh between 6am to 10pm, 0.12€/kWh otherwise) and the feed-in tariffs (0.06€/kWh with an unpredictable evolution). This is depicted by figure 6 that shows the economic result of each installation using the French prices. In these results we see that most cases are not profitable if we consider constant prices. General trends, however, show that, at least in France, electricity prices from the Grid will steadily increase over the year — we can reasonably expect 5% per year. It is therefore likely that the installation will be easier to amortize in practice. We can easily integrate these factors into our model, but this would make the figure difficult to read here.

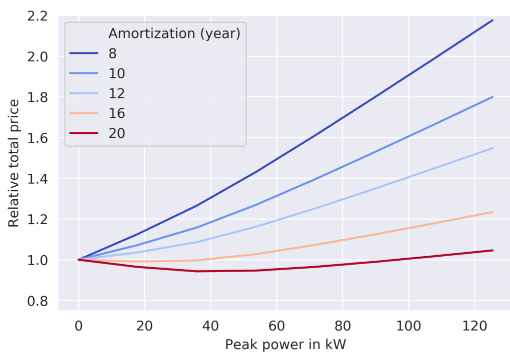


Fig. 6. Economic comparison of the installation over the two-year period. We see that considering a constant price makes almost all installations not profitable except installing less than 40kWp of local generation with an amortization of 16 or 20 years.

Given realistic price inputs we managed to estimate the profitability of various installations considering various amortization duration. In the rest of the paper, we will see how to improve these results by adding batteries and by optimizing schedules. To this end, we will consider an installation of 50kWp. This size is interesting because it leaves flexibility producing more than 20% of production in energy excess that could be used in energy storage.

B. *Energy storage*

This section evaluates the impact of adding storage to our 50kWp installation in order to enable the use of excess production outside production periods. Energy storage devices come in all forms and shapes. For an industrial case a few aspects are important: the **energy density** that determines the size of the installation, the **number of cycles** that impacts the usage and the lifetime of the battery, and **the price per kWh**, which is depending on the energy efficiency and on the storage system itself.

Lithium and Vanadium Redox are commonly available battery types that are well suited to industrial case. We compare some of these specifications in Table I based on information available online. These numbers give an order of magnitude since they will vary from a manufacturer to another. Lithium batteries have a much higher density, which is important for mobile devices such as smartphones or electric vehicles but is less important for industries, especially in rural environment where land is cheaper. The number of cycles is more than ten times more important for Vanadium Redox batteries. We consider one complete cycle to be from full state of charge, to complete discharge then full charge again.

TABLE I
LITHIUM AND VANADIUM REDOX BATTERY COMPARISON.

	Lithium	Vanadium Redox
Density (Wh/kg)	100 to 250	20
Number of cycle	1,200	15,000 to 20,000
Efficiency (%)	90	75 to 80
Cost (€/kWh)	1000	500

An interesting result from our previous simulation is the average daily energy excess from the local production. In view of adding batteries, an expert might wonder if it is worth installing more generation to increase energy excess. He would also be interested in the following questions: what type of battery is the most suited for a given site? What is the optimal battery capacity? What is the optimal inverter nominal power? These are the questions we will address in the following simulations.

Our simulator makes some **assumptions regarding batteries and their usage**. These assumptions can be tweaked by developing plugins to represent more specific aspects of real world devices. For example, the efficiency is considered constant regardless of the state of charge of the battery. Battery wear could be set to decrease the maximum capacity of a battery from its usage. We also choose to charge the batteries from the excess energy of our local production only. Batteries could be charged using the grid if it happens to be cheaper, depending on the input prices. This ability to change and extend the behaviour of the system is important because it is difficult to predict all cases of use a priori.

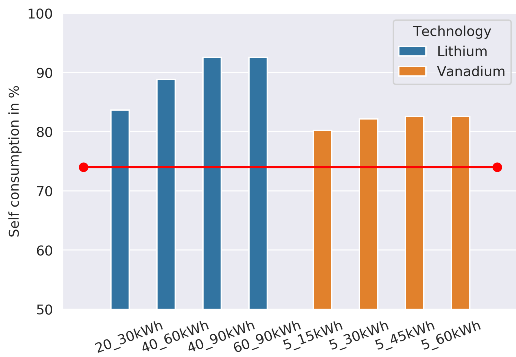
In our simulation, we selected four variants of the two types of battery commonly available from sellers. Their characteristics are described in Table II. We ignored lead-acid batteries because they do not offer enough flexibility: they cannot be discharged below a certain threshold without deteriorating. We will run simulations for our production of 50kWp, using one of each of these batteries. Our objective is to see if the use of batteries increases the autonomy of the site.

TABLE II
BATTERY SPECIFICATION SELECTED FOR SIMULATION IN OUR USE CASE.

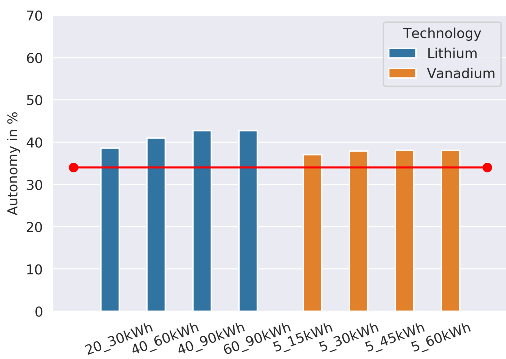
Lithium		Vanadium Redox	
Inverter Power	Capacity	Inverter Power	Capacity
20kW	30kWh	5kW	15kWh
40kW	60kWh	5kW	30kWh
40kW	90kWh	5kW	45kWh
60kW	90kWh	5kW	60kWh

The impact on self-consumption is displayed in Figure 7a. It shows that self-consumption is increasing, which is logical since the excess is used. Yet, contrary to expectations, autonomy only increases very marginally in 7b — including for large battery models. To obtain a reasonable autonomy level, a very large number of batteries would have to be added. Even with the best battery here (lithium 40_90kWh), the costs involved would make the system completely uneconomic. There is no difference between 40 and 60kWp because there is no production peak big enough. Considering

Vanadium, we can observe the opposite: since the inverter power stays constant and increasing the capacity does not do anything we can deduce that our energy excess happens in short duration and with peaks bigger than 5kW.



(a) Impact on self consumption. The higher the less energy is lost or injected on the Grid.



(b) Impact on autonomy. The higher the less energy is taken from the grid

Fig. 7. Batteries impact on energy efficiency, first number is the power of the inverter in kW, second the capacity of the battery in kWh. The red line is the level of our optimal with 50kWp of solar panels and no batteries.

In Table I, the number of battery charge cycles performed in each simulations might give an expert an estimation of the total life time of our battery system and help set a budget. While being quite expensive, energy storage systems do not improve significantly the autonomy of a site. However, the impact on self consumption is greatly improved, even with the smallest capacity. Self-consumption is important if we want to reduce greenhouse-gas emissions because it promotes the use of energy produced by solar panels. Yet, it is really detrimental to profitability and in our case probably unrealistic. We propose in the following to investigate the impact of load shifting.

C. Optimizing activity schedule

In the first Section IV-A we investigated production only, in the next Section IV-B we explored the use of energy storage. The last aspect to consider is the consumption and its optimization. In this use case we are evaluating the consumption of all the industrial processes of a single farm. Experts know the variability allowed by a process and by talking with an industrial user, they can understand its setup. Comparing this variability to the efforts needed in order to re-organize a process comes at a cost. In this section we call *shiftable share* the maximum share of daily energy that we are allowed to move during the same day.

The Figure 8 shows several realistic cases for a calculation ranging from 5 to 20%. This interval is based on the activities described by the operator and on the experience of similar farms. For this site, in practice, at least 10 to 15 percent of the activity can be automated (e.g., producing hot water, producing ice or managing lighting), while a ten percent adjustment may be recommended to the operator depending on the weather. We simulate two types of scenarios: the optimization of activities without batteries and the optimization with batteries (one of 30kWh and the other of 90kWh).

Without any batteries, we see in Figure 8 that the autonomy grows steadily if we increase the shiftable share because we directly move consumption to more appropriate periods — see Figure 3 for an illustration. Setting the appropriate share is the important task of experts: under evaluating it will lower the expected results and over evaluating it will give tremendous but impossible results. Mixing optimization and batteries also improve the global autonomy. Both approaches use the energy excess from the production, correctly sizing the solar panels to leave enough energy excess for optimization is part of the trade-off analysis. In Table III we see that increasing the local production from 50kWp to 90kWp can be relatively profitable if we consider a process optimization while reaching up to 58% of autonomy.

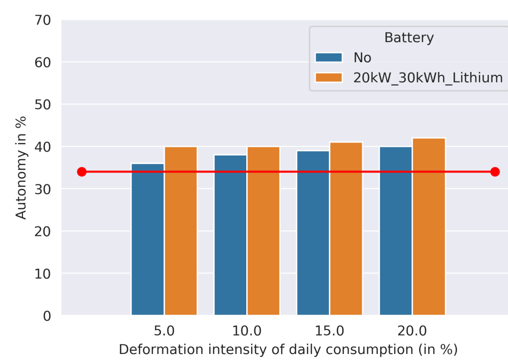


Fig. 8. Impact of Demand Response on Autonomy. Red line is the autonomy of our optimal case with 50kWp of local production.

We observe here that if batteries are useful to increase autonomy, the shifting of activities alone already allows a very significant gain while being much more affordable. For this reason, when profitability is the priority, energy management systems such as demand response should be considered first.

D. Lesson learned

This case study, based on production and real consumption data, allows us to observe several phenomena summarized in Table III:

1) the compromise between battery size, installation size and activity optimization is well balanced. No

TABLE III

COMPARISON OF VARIOUS INSTALLATION SOLUTIONS IN TERMS OF AUTONOMY FROM THE GRID AND RELATIVE COST OF USING ONLY THE GRID. LESS THAN 1 MEANS THAT THE SOLUTION IS PROFITABLE WITHIN 15 YEARS CONSIDERING A BATTERY REPLACEMENT.

		Prod. 50kWp		Prod. 90kWp	
Solution		Autonomy (%)	Cost	Autonomy (%)	Cost
	PV	34	0.92	40	1.03
PV +	B1	38.6	1.03	45.9	1.13
	B2	42.7	1.11	53.57	1.32
	PV + O	39.9	0.86	48.7	0.94
PV + O +	B1	41.7	0.99	52.2	1.06
	B2	44.2	1.24	58.3	1.27

PV: photovoltaic panels, O: process optimization, B1: lithium battery, 20kW inverter and 30kWh capacity, B2: lithium battery 40kW, inverter and 90kWh capacity.

single parameter optimization can maximize self-consumption and minimize power costs. Neither batteries, nor the shift in activities, nor the increase in the solar panel size are in themselves perfect answers to make self-consumption profitable in France. However, a balanced optimization could be profitable without any incentive from the local government.

2) Our simulator can finely explore the entire spectrum of input parameter values in a reasonable amount of time. (around 3 to 6 minutes for two years simulation on a simple laptop).
3) Benefiting from a Domain Specific Language to model the activity makes it possible to finely target process that can be shifted and the one that cannot. That avoids overestimating the gain associated with these shifts.

V. CONCLUSION

In this paper we present a case study to illustrate how a model-driven engineering approach can be used by energy experts to model process shifting capabilities, to optimize local generation and energy storage in order to estimate the profits and improve greenness of a site using local generation. This approach can be used either before any installation of equipment or to optimize an existing site. Simulations try to meet final user needs and constrains in term of: grid autonomy, electricity bill, installation cost or even amortization duration. To illustrate the approach, we use a real world case study with an agricultural site with solar panels, lithium and redox vanadium batteries. Based on two years real-data of power-consumption and local generation, we simulate various load shifting scenarios and compare their results to the addition of expensive equipment (new solar panels, new batteries, ...). We show that focusing only on production requires a good understanding of process consuming energy to be both profitable and autonomous or to choose the right renewable sources. Through these data, we illustrate that the optimization of only one parameter (local generation, storage or process shifting) cannot by itself maximize self-consumption and minimize power costs. We also show that correctly sizing energy storage and choosing the right battery technology is challenging. A simulator with several battery model helps to compare and correctly select the right energy storage system. Load shifting and energy management systems in general can be as energy efficient as batteries but requires more knowledge of the final user activity domain.

Future work will consider extending our model and its notion of energy to manage other resources such as ice or hot water. It would help explore optimization paths by using more resources as batteries and thus lead to more energy reduction.

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